3B2v7.51c GML4.3.1 JEPO : 1476 Prod.Type:FTP pp.1–8(col.fig.:2,3,5) ED:Nagesh PAGN: ashok SCAN: Mangala

ELSEVIER

Energy Policy ▮ (▮▮▮▮) ▮▮▮–▮▮▮

ENERGY POLICY

www.elsevier.com/locate/enpol

Letting the (energy) Gini out of the bottle: Lorentz curves of cumulative electricity consumption and Gini coefficients as metrics of energy distribution and equity

Arne Jacobson[a], Anita D. Milman[a], Daniel M. Kammen[a,b,*]

[a] University of California, Berkeley, Energy and Resources Group, 310 Barrows Hall 3050 Berkeley, CA 94720 USA
[b] Goldman School of Public Policy University of California, Berkeley, USA

Abstract

Energy services are fundamental determinants of the quality of life as well as the economic vitality of both industrialized and developing nations. Few analytic tools exist, however, to explore changes in individual, household, and national levels of energy consumption and utilization. In order to contribute to such analyses, we extend the application of Lorenz curves to energy consumption. We examined the distribution of residential electricity consumption in five countries: Norway, USA, El Salvador, Thailand, and Kenya. These countries exhibit a dramatic range of energy profiles, with electricity consumption far more evenly distributed across the population in some industrialized nations than others, and with further significant differences in the Lorenz distribution between industrialized and industrializing economies. The metric also provides critical insights into the temporal evolution of energy management in different states and nations. We illustrate this with a preliminary longitudinal study of commercial and industrial electricity use in California during the economically volatile 1990s. Finally, we explore the limits of Lorenz analyses for understanding energy equity through a discussion of the roles that variations in energy conversion efficiency and climate play in shaping distributions of energy consumption. The Lorenz method, which is widely employed by economists to analyze income distribution, is largely unused in energy analysis, but provides a powerful new tool for estimating the distributional dimensions of energy consumption. Its widespread use can make significant contributions to scientific and policy debates about energy equity in the context of climate change mitigation, electric power industry deregulation and restructuring, and the development of national infrastructure.

Keywords: Energy consumption; Equity; Electricity; Inequality

1. Introduction

Energy consumption has long been seen as a critical indicator of socioeconomic opportunity, national economic activity and growth, and as a key factor in the human impact on the environment. A number of measures of energy usage, most of which rank energy consumption on a per capita or per productivity basis (e.g. kWh/capita, kWh/GDP), are widely used for tracking national economic performance as well for measuring development [1]. Beyond these crude measures, however, few analytic tools exist to examine the interactions between economic activity and energy services, to examine the temporal evolution of energy infrastructure, and to examine the economic and social returns on energy investments. The use of disaggregated consumption data to analyze distributions of energy consumption is extremely rare (see, Saboohi, 2001 for a recent example of work that includes disaggregated energy consumption data). However, the significance of energy distribution trends—including equity related

*Corresponding author. University of California, Berkeley, Energy and Resources Group, 310 Barrows Hall 3050 Berkeley, CA 94720 USA. Tel.: +1-510-642-1139; fax: +1-510-642-1085.

E-mail address: kammen@socrates.berkeley.edu (D.M. Kammen).

[1] The World Bank charts total national energy and electricity production in their national development report (http://www.world-bank.org/data/), and the International Energy Agency (http://www.iea.org/statist/index.htm) provides somewhat more detailed breakdowns for the economies of most nations. Many national energy agencies provide similar statistics, but virtually all are simple national aggregates.

0301-4215/$ - see front matter © 2004 Elsevier Ltd. All rights reserved.
doi:10.1016/j.enpol.2004.02.017

trends—cannot be determined without consideration of disaggregated data.

We propose a set of methods that utilize Lorenz curves, which are commonly used by economists to estimate income inequality but which are largely unused in energy analysis, as a key analytical tool that combines energy access and consumption into a single metric. This metric allows for inter-country comparisons while simultaneously providing information about intra-country distributions of energy consumption. Perhaps even more importantly, Lorenz curves can be used in longitudinal studies to identify distributional trends in a country or region. Longitudinal analyses are particularly important as a tool for understanding changes in energy equity due to policy shifts, to explore the often complex relationships between patterns of energy consumption and economic trends, and to examine the potential returns on investment in national or regional energy infrastructure programs.

2. Energy Lorenz curves and Gini coefficients

Lorenz curves and Gini coefficients are widely used in economics to estimate income inequality (Gastwirth and Glauberman, 1976). In this article we use these metrics to estimate distributions of energy consumption. The Lorenz curve is a ranked distribution of the cumulative percentage of the population of recipients on the abscissa versus the cumulative percentage of the resource distributed along the ordinate axis. The greater the distance this curve is from the diagonal line extending from the origin to the point with coordinates $x = 1$ (or 100%), $y = 1$ (or 100%), the greater the inequality in energy consumption. The Gini coefficient is a numeric measure of inequality that reveals the difference between a uniform distribution and the actual distribution of a resource. It is calculated from the Lorenz curve by taking the ratio between (a) the portion of the area enclosed by the diagonal line and the Lorenz curve and (b) the total area under the diagonal line of uniform distribution. Formally, the Gini coefficient for energy consumption is calculated as

$$G_e = 1\text{-}\sum_i (Y_{i+1} + Y_i)(X_{i+1} - X_i),$$

where X_i is the number of energy users in population group i/total population and Y_i the quantity of energy used by population group i/total energy use with Y_i ordered from lowest to highest energy consumption. The Gini coefficient ranges from perfect equity among all members of the population ($G_e = 0$) to complete inequity ($G_e = 1$). As more than one Lorenz distribution of a resource can lead to the same Gini value, it is often useful to employ both metrics simultaneously.

3. Lorenz curves and energy equity

Lorenz curves provide a quantitative measure of differential amounts of energy consumption, but do not directly measure the differential utility of energy *services*. As an example, the same amount of energy may be consumed differently in the form of varied energy services (e.g. lighting, heating, appliances), or as a result of various efficiencies of the technologies employed. Quantities of energy are a reasonable measure of utility when (a) the average overall efficiency among consumers is approximately constant, (b) the marginal benefit from a unit of energy (e.g. a kWh) from consumer to consumer is roughly consistent.

There are, of course, some situations for which these conditions do not hold. For example, a quantitative comparison of the energy consumed by families that rely primarily on fuel wood for cooking with families that use propane gas reveals that wood based cooking requires far more energy even though most would agree that cooking with gas is preferable. Hence in this case the lower level of energy consumption corresponds with a higher level of benefit.

Yet there are also a large set of situations for which quantitative measures of energy consumption can be used effectively to estimate energy equity. This is especially true in cases in which a single energy source is considered (e.g. residential electricity consumption or petrol use for private transportation) and where average per consumer conversion efficiency is approximately constant. Finally, in non-equity related distributional studies of energy market consumption trends or other similar issues these constraints (i.e. constraints (a) and (b) listed above) generally do not apply.

In the case of US residential electricity consumption, the marginal benefit of electricity consumption appears to be roughly constant over a range of consumption levels for grid connected residential users. This is seen in Fig. 1, which depicts the relationship between purchasing power and electricity consumption over a wide range

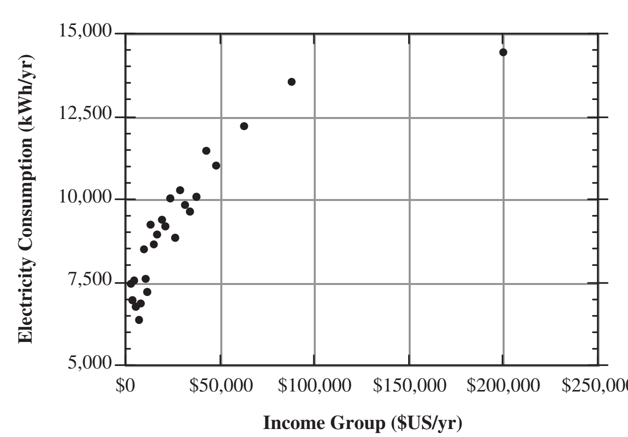

Fig. 1. Household electricity versus income for the US in 1997.

of consumption levels. In this figure, that relationship is approximately linear over a range of consumption levels representing the majority the population, and then levels off, suggesting diminishing returns.[2] Thus, most situations involving grid connected residential consumers fall in the linear portion of the curve and so the assumption of a roughly constant marginal benefit may be valid.

However, for very small and large consumption levels the marginal benefit appears to result in disproportionately large and disproportionately small levels of benefit, respectively. Fig. 1 demonstrates this relationship at the ''high end'' in a US context. At the low end (small quantities of consumption) this can be observed through high willingness to pay among the rural poor in developing countries for very small quantities of energy (e.g. $50/kWh or more for tiny quantities of energy from dry cell batteries; $1–$2/kWh for 5 kWh per month for solar electricity; but only on the order of $0.10–$0.20/kWh for larger quantities of energy from electricity grids see Jacobson, 2004). This range in willingness to pay represents decreasing marginal utility for larger quantities of energy.

4. Cross country comparisons highlight differences in electricity equity

To illustrate the application of the Lorenz and Gini metrics we have performed a distributional analysis of residential electricity use for a mix of industrialized and industrializing nations (Fig. 2). In each case we generated Lorenz curves as well as the associated Gini coefficients using residential electricity consumption survey data that divided the households into groups according to their consumption levels. We present additional population, income, and energy data for these five countries in Table 1. These countries, Norway, the United States, El Salvador, Thailand, and Kenya, were selected based on a combination of geographic

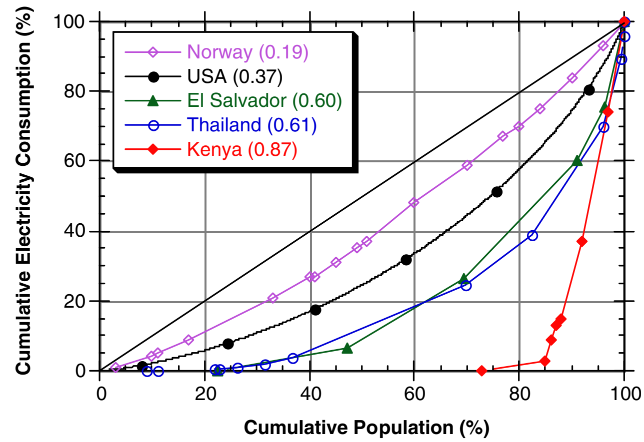

Fig. 2. Lorenz curves for residential electricity in five countries. The Gini coefficients for residential electricity consumption are presented in the legend of the graph in parenthesis.

diversity, a desire to include countries with varying degrees of economic development, and data availability. The degree of disaggregation of the population into consumption groups varied from country to country, but in general we were able to generate reasonable curves with as few as six groups[3].

The Lorenz curves in Fig. 2[4] reveal dramatic differences in the intra-country distribution of residen-

[2] A regression analysis for all of the data points in Figure 1, except the one representing households at the $200,000 annual income level, indicates that a linear model provides a reasonable explanation of the relationship between income and electricity consumption ($r^2 = 0.87$). However, a statistical analysis comparing that model with a quadratic polynomial model indicates that the addition of a quadratic term in the regression analysis provides a better fit to the same data ($p<0.01$). Strictly speaking, this supports the interpretation that energy consumption has declining—not constant—marginal returns. We contend, nonetheless, that approximately linearity (i.e. approximately constant marginal utility) over a broad section of the population is sufficient for Lorenz curves to provide a useful metric of energy equity. This position is consistent with common practice in the use of the Lorenz metric with other resources and commodities. For example, monetary income is widely accepted to have decreasing marginal utility, and Lorenz curves are commonly used as a measure of income equity.

[3] The data sets for the respective countries had the following degrees of aggregation. (See note 7 for data source references). Norway: national level data for 1995 aggregated into 20 sub-groups according to income and dwelling size; USA: survey data from 1997 for a nationally representative weighted sample of 5900 homes; El Salvador: national level data for 2001 aggregated into six groups according to monthly electricity consumption; Thailand: national level data for January, 2000 aggregated into 11 groups according to monthly electricity consumption; Kenya: survey data from 2000 for a nationally representative sample of 2300 homes. For El Salvador, Thailand, and Kenya we added an additional category for households with no electricity access (i.e. these households had zero consumption). In addition, we estimated off-grid electricity consumption in households (i.e. from generators, solar energy systems, car batteries, etc.) for Thailand (source, C. S. Greacen, personal communication) and Kenya (*source*: field research data by author A. J.). In each case we generated the Lorenz curves by ordering the aggregated groups for each country by increasing per household electricity consumption. We then plotted electricity consumption as a function of population, where population is defined by the number of households. We chose to define population in terms of the number of households because data on household size for the different consumption groups were not available for several of the countries. In those countries where information about household size was available, the inclusion of these data did not result in significant changes in the analysis.

[4] The data for the Lorenz curves in Fig. 1 come from the following sources: Norway (1995 data from A.C. Bøen, R. Nesbakken, *Energibruk til stasjonćre og mobile formål per husholdning 1993, 1994 og 1995*, Statistics Norway, Olso, 1999, http://www.ssb.no/emner/01/03/10/rapp9922/rapp9922.pdf); USA (1997 data from US EIA, *1997 Residential Energy Consumption Survey (RECS)*, http://www.eia.doe.gov/emeu/recs/contents.html); El Salvador (2001 data from SIGNET, *Avances Estadisticas 2001*, www.signet.com.sv); Thailand (January, 2000 from National Energy Policy Council of Thailand, Cabinet resolution of October 3, 2000); Kenya (2000 data from Kamfor

Table 1
Population, income, and energy data for five countries

Country	Population (millions)	GDP/capita ($US, PPP adj.)	Income Gini Coeff.	Annual Electricity Per Capita (kWh)	Residential Electricity Access (%)	Energy Gini Coefficient
Norway	4	20,800	0.26	27,000	>99	0.19
USA	284	28,600	0.41	12,000	>99	0.37
El Salvador	6	4000	0.52	540	77	0.60
Thailand	61	6400	0.41	1,300	81	0.61
Kenya	31	1600	0.45	130	15	0.87

tial power consumption between the nations. This can be seen through a comparison of the fraction of the population of each country that accounts for half of the total electricity consumption. Norway, where half of residential electricity is used by the top 38% of the household customers, has the most evenly distributed electricity consumption pattern. It is followed by the USA, where half of the electricity is consumed by about 25% of the households, then El Salvador (≈15%), Thailand (≈13%), and Kenya (≈6%).

Although a complete analysis of the reasons for the differences between the respective distributions is beyond the scope of this article, it is clear from a preliminary analysis—including information presented in Table 1[5]— that the distributional characteristics of household electricity consumption for the respective countries represented in Fig. 2 depend heavily on a combination of the countries' wealth, income distribution, and historical government infrastructure building policies. The range of additional factors that shape the Lorenz curves, including climate, energy efficiency measures, and the size and geographic distribution of a country's rural population, can provide important constraints on the shape of the curves, and is an area of current investigation. This highlights the importance of using energy Lorenz curves and Gini coefficients in combination with broader analyses—including both quantitative and qualitative analytical techniques—of the associated processes and factors that influence the distribution of energy consumption in the respective countries.

5. Energy efficiency, Lorenz curves, and equity

We noted previously that the efficacy of this method for estimating energy equity depends in part on the degree of variation in the average energy conversion efficiency among households in a given country or region. In order to estimate the significance of this "efficiency effect" we carried out a sensitivity analysis of the Lorenz distribution to variations in energy conversion efficiency for residential electricity consumption in the USA.[6] We used results from the 1997 "Scenarios of US Carbon Reductions: Potential Impacts of Energy-Efficient and Low-Carbon Technologies by 2010 and Beyond" study carried out by the US Department of Energy[7] to estimate the boundary conditions for the potential variation in conversion efficiency among US households.

The DOE report estimates an upper bound for potential energy savings for a typical household that adopts a set of currently available energy efficiency measures. We aggregated the results from this study into use categories consistent with the US EIA 1997 household electricity consumption data set used in this article to generate the following boundary conditions for inter-household electricity conversion differences: Space conditioning =20.5%; refrigeration and freezing =30.5%; water heating =28%; other uses (including lighting, household appliances, cooking, and others) =36%. These numbers reflect the mean percent difference in energy conversion efficiency between

(footnote continued)
Company Ltd., *Study on Kenya's Energy Demand, Supply and Policy Strategy for Households, Small Scale Industries and Service Establishments*, Ministry of Energy, Kenya, 2002). See also text note 8.

[5]The data in Table 1 and Fig. 1 for each country are given for a particular year. The year varies from country to country depending on the availability of disaggregated residential electricity consumption data for the Lorenz curves. The years for each country are as follows: Norway, 1995; USA, 1997; El Salvador, 2001; Thailand, 2000; Kenya, 2000. Data sources for Table 1 include http://devdata.worldbank.org/dataquery (all data from this source except for following items as noted), http://www.cia.gov (GDPpc data), http://signet.gov.sv (El Salvador kWhpc), http://www.iea.org/pubs/reviews/files/nor97/nor06.htm (Norway kWhpc), http://www.iea.doe.gov/emeu/aer/txt/stb0801.xls (USA kWhpc), http://www.umsl.edu/services/govdocs/wofact95/wf950182.htm (Norway population), http://earthtrends.wri.org/ (income Gini data for all countries).

[6]The authors wish to thank an anonymous reviewer for pointing out the utility of this analysis.

[7]Scenarios of U.S. Carbon Reductions: Potential Impacts of Energy-Efficient and Low-Carbon Technologies by 2010 and Beyond Report number LBNL-40533 or ORNL/CON-444, September 1997. Prepared by the Inter-Laboratory Working Group on Energy-Efficient and Low-Carbon Technologies: US Department of Energy (DOE): Oak Ridge National Laboratory, Lawrence Berkeley National Laboratory, Argonne National Laboratory, National Renewable Energy Laboratory, Pacific Northwest National Laboratory.http://enduse.lbl.gov/Projects/5Lab.html

Table 2
Sensitivity analysis for the influence of energy efficiency on Gini coefficients for US residential electricity consumption in 1997.

Scenario	Electricity Gini	Change in Gini from baseline (%)	Overall efficiency adoption rate among all HH%	Average electricity savings among all HH%
Baseline	0.37	n/a	0	n/a
A	0.44	19	20	15
B	0.28	−24	60	14
C	0.39	7	65	26
D	0.32	−12	65	19
E	0.38	4	35	16
F	0.34	−8	35	11
G	0.36	−2	35	14

Scenario definitions:
Scenario A: Larger consumers are most efficient: 100% of households (HH) in the top quintile adopt efficiency measures, while 0% of HH in the bottom four quintiles adopt efficiency measures.
Scenario B: Smaller consumers are most efficient: 100% of HH in the bottom three quintiles adopt efficiency measures, 0% of HH in the highest two quintiles adopt efficiency measures.
Scenario C: 65% total adoption of efficiency measures across population; larger consumers are more efficient; from bottom to top quintiles efficiency measures are adopted by 30%, 50%, 65%, 85%, and 95% of the households, respectively. The 65% rate corresponds with the DOE study's upper bound for efficiency adoption.
Scenario D: 65% total adoption of efficiency measures across population; smaller consumers are more efficient; from bottom to top quintiles efficiency measures are adopted by 95%, 85%, 65%, 50%, and 30% of the households, respectively. The 65% rate corresponds with the DOE study's upper bound for efficiency adoption.
Scenario E: 35% total adoption of efficiency measures across population; larger consumers are more efficient; from bottom to top quintiles efficiency measures are adopted by 16%, 26%, 36%, 46%, and 51% of the households, respectively. The 35% rate corresponds with the DOE study's most likely efficiency adoption scenario.
Scenario F: 35% total adoption of efficiency measures across population; smaller consumers are more efficient; from bottom to top quintiles efficiency measures are adopted by 51%, 46%, 36%, 26%, and 16% of the households, respectively. The 35% rate corresponds with the DOE study's most likely efficiency adoption scenario.
Scenario G: 35% total adoption of efficiency measures across population; middle and upper middle range consumers are more efficient, while the smallest and largest consumers are less efficient. From bottom to top quintiles the adoption rates are 25%, 30%, 45%, 50%, 25%, respectively. The 35% total adoption rate corresponds with the DOE study's most likely efficiency adoption scenario.

groups of households that use the most energy efficient technologies available and those that use the average technologies which are more widely deployed.[8] These boundary conditions were then used to create six scenarios characterized by different distributions of energy conversion efficiency across the population of households.

For each scenario, the households in each quintile of electricity consumption were assigned a percentage deployment of the maximum potential energy conversion efficiencies outlined above. The electricity consumed by households in that quintile was then adjusted to account for the increased level of service from the use of a given quantity of electricity that is associated with a higher conversion efficiency. A selected set of scenarios, including the two which generated the greatest overall changes in the Lorenz distribution, are presented along with the original baseline case in Table 2.

Scenarios A and B represent the extreme case in which only a small segment of the population adopts efficiency measures and the rest of the population does not. The other scenarios represent more realistic assumptions, matching the DOE study's prediction of 35% of US households adopting high efficiency practices as the most likely scenario (scenarios E, F, and G), and 65% adopting those practices as an upper bound for efficiency adoption (scenarios C and D). Scenarios A and B indicate that extreme variations in the adoption of energy conversion efficiency measures could result in changes in electricity Gini coefficients on the order of 20 to 25%, while the more moderate cases presented in scenarios C, D, E, F, and G indicate that in practice the "efficiency effect" is likely to be considerably smaller. The impact of these scenarios on the distribution of energy consumption is demonstrated graphically in Fig. 3. Scenario G may represent a "most likely" scenario in which mid-level consumers are more efficient on average, while the smallest and largest consumers are less efficient. This corresponds to greater levels of efficiency adoption among middle class users than among the poor (many of whom perhaps cannot afford higher efficiency devices) and the rich (who may place a low priority on efficiency because energy costs are a small fraction of their total expenditures).

[8] Although individual households may have larger or smaller differences in energy conversion efficiencies than those reported here, the household data we use is a weighted statistical sample of 5898 US households. The survey was designed so that each household in the data set represents a group of approximately 15,000 homes; therefore applying these percentages to the data is tantamount to assuming that these are the *maximum average differences in efficiency* between these *groups* of households.

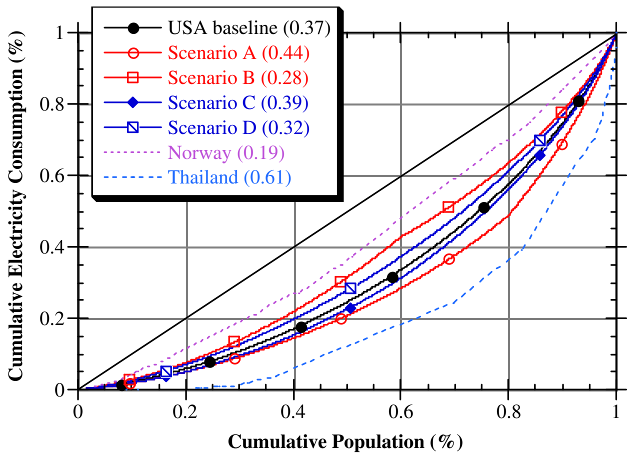

Fig. 3. Lorentz curves for sensitivity to differences in energy efficiency among residential users in the USA. Note that scenarios E, F, and G have been omitted from Fig. 3, as these curves are nearly indistinguishable from the baseline case.

This analysis—particularly scenarios C through G—suggests that in the case of this US data set, differences in energy efficiency among households play only a minor role in influencing the marginal benefit of energy use. The scale of this ‘‘efficiency effect’’ may vary in other contexts and continued research is warranted, but our analysis here supports the case for the use of the Lorenz metric for estimating energy equity.

6. Climate, Lorenz curves, and equity

Along with energy conversion efficiencies, climate can play an important role in influencing patterns of residential electricity consumption. Climate can influence the distribution of energy consumption in two main ways. First, in countries with extreme heating or cooling loads, the energy used for climate control may make up a large and relatively inelastic fraction of energy consumption. Such a dynamic would tend to reduce differences in consumption among households, with a corresponding flattening in the shape of the Lorenz curve. This dynamic likely plays a role in Norway's relatively even Lorenz electricity distribution (see Fig. 2), although other factors including government policies and a relatively even income distribution may play an even greater role.

Second, large variations in climate within a country could result in significant differences from region to region in average household heating or cooling related consumption. While this is unlikely to be an important factor in countries with relatively small variations in regional climate (e.g. Norway, El Salvador, Thailand, Kenya), it can be a significant factor in larger countries with wide climate variations such as the US. In fact, as illustrated in Fig. 4, regional data from the US indicate that average household electricity consumption in some southern states is roughly twice that in New England. These regional differences may be in part due to climate and in part due to the mix of fuels used for heating and cooling in the respective regions.[9] However, few countries have the combination of climate diversity and the high levels of energy use for heating and cooling that are present in the United States. As such, climate likely plays a larger role in influencing the shape of the residential electricity Lorenz curve in the US than it will in nearly any other country. This is true because other countries with wide climate variations such as China do not yet use electric heating or cooling to a degree that would influence the Lorenz household electricity distribution in a significant way. Further research on the role of climate in shaping energy distributions is warranted, but this brief discussion suggests that while the effect of climate may be important in a few cases and especially in the US, it is likely small in most countries.

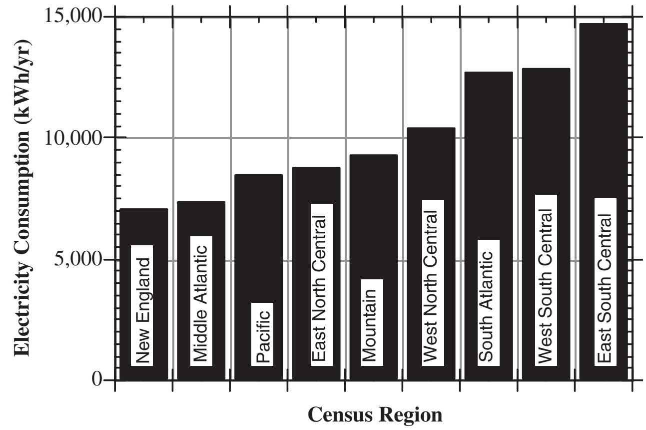

Fig. 4. Mean household electricity consumption by Census Division for the US in 1997. The figure indicates that households in southern areas tend to consume more electricity than those in northern areas.

7. Longitudinal studies indicate temporal changes in distributions of energy consumption

The use of the proposed energy Lorenz curve and Gini coefficient metrics are not limited to cross country comparisons. They are perhaps even more useful in the context of longitudinal studies which evaluate changing distributional characteristics of energy use within a country or region over time. Longitudinal studies of a single region involve comparisons between cases that

[9] Regression analyses indicate that climate (in the form of heating and cooling degree days), a dummy variable for the census divisions reported in Fig. 4, and household income all have statistically significant correlations with electricity consumption levels ($p < 0.001$). Note that regional location did not co-vary with income, while regional location did, of course, co-vary strongly with both heating and cooling degree days. These results suggest that in the US income and climate may both play important roles influencing the distribution of residential electricity consumption.

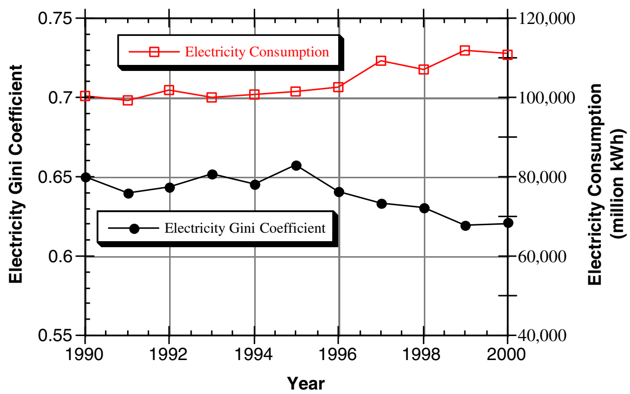

Fig. 5. Gini coefficients and total electricity consumption for commercial and industrial accounts in California from 1990 to 2000 (S3).

include fewer potentially confounding variables than cross country studies. The Lorenz and Gini metrics may be particularly appropriate for use in ‘‘before and after’’ studies to evaluate the equity dimensions of power sector reform and other major policy decisions that reshape the economic and regulatory context of the delivery of energy services.[10] Furthermore, Lorenz and Gini metrics are also useful in distributional studies that are not strictly related to equity. This can be observed through a case study of commercial and industrial electricity consumption in California during the 1990s. This approach, particularly when combined with an independent evaluation of economic trends, provides a powerful tool for analysis and forecasting future demand trends in the electricity sector.

Fig. 5 presents electricity consumption data along with changes in the Gini coefficient for commercial and industrial electricity use in California from 1990 to 2000.[11] Data for commercial and industrial customers were divided into over 1000 electricity consumption groups according to Standard Industrial Classification codes, which were then ordered per customer account by increasing electricity consumption. These data show relative stability in consumption levels and the distribution of electricity use among small and large firms from 1990 to 1995, but thereafter consumption increases while the Gini coefficient drops 4% points to 0.62 in 2000.

This decrease in the Gini coefficient indicates that as consumption grew, smaller commercial and industrial consumers accounted for a relatively larger share of overall electricity use. This distributional change may correspond with a shift in the economy towards an increasing role for smaller firms during the ‘‘technology boom’’ of the late 1990s (Castells, 1996). In the context of the ‘‘globalizing’’ economy, many large corporations are increasingly using smaller subcontractor firms to carry out job tasks that they formerly did themselves in-house. The shift of this business from large to smaller firms may account for some of the shift in the distribution of commercial and industrial electricity use observed in Fig. 5. However, this is only one possible explanation, and it is likely that other factors also contributed to the observed trend. In any case, analyzing the root causes of this trend is not the main focus of this paper. Rather we wish to demonstrate the usefulness of longitudinal studies for identifying changes in the distribution of energy consumption which can then be further investigated with additional analyses to determine causality.

8. Extending the metric from electricity to energy

While the examples presented above focus on distributions of *electricity* use, Lorenz curves and Gini coefficients can also be applied to electricity generation as well as other forms of energy consumption. For example, the a of Lorenz curves to electricity generation may indicate changes in the relative prevalence of small and large-scale power producers as electricity markets are restructured. Additionally, temporal studies of the distribution of fuel consumption for private transportation could reveal important equity changes related to national fuel efficiency policy, consumer trends, and gasoline prices.

9. Contributions of this new metric

As we enter the 21st century there is a pressing need to develop our ability to effectively manage non-renewable and renewable resources, as well as to understand the impacts of energy technologies on society and the environment. This is particularly critical as the human capacity to fundamentally alter the biosphere increases. The distribution of energy resources and services may result in significant social, economic, and environmental inequalities. The Lorentz and Gini energy metrics provide a new perspective that can be used to greatly expand our understanding of the inter-relationships between human actions and energy systems. As such, they are a key tool in what has been aptly termed ‘‘sustainability science’’ (Lubchenko, 1998). The proposed energy Lorenz curve and Gini coefficient metrics have much to offer for evaluating the distributional dimensions of energy use both within and between nations, as well as a means to chart the impacts over

[10] In conducting such a study, it is important to acknowledge that many processes and factors may contribute to changes in the distribution of energy consumption in a country or region and that correlation between a change and the implementation of a policy does not necessarily indicate causation.

[11] Data from 1990 to 2000 provided courtesy of the California Energy Commission (CEC).

time of new energy technologies, methods of distribution, markets, and policies. Their widespread use—in combination with broader analyses that seek to understand the social, historical, economic, and spatial processes that generate the underlying distributional trends—can make a significant contribution to key debates about energy, the environment, and development.

Acknowledgements

It is a pleasure to thank the many colleagues who assisted in identifying and accessing the data needed for this analysis. We thank: Runa Nesbakken (BM Statistics Norway Library and Information Centre, Norway); Andrea Gough (CEC, California); Chris and Chuenchom Sangarasri Greacen (Thailand); Alex Enrique Varela (SIGNET, El Salvador), Dr. Ing. Salvador E. Rivas (El Salvador); Mbiri Gikonyo (Kamfor Company, Ltd., Kenya); Reuben Deumling, Alexander Farrell, Rebecca H. Ghanadan, Karen Herter, Isha Ray, and Steve DeCanio (University of California). We gratefully acknowledge the support of the Energy Foundation (to D. M. K.), and Judith Iklé, Supervisor, Federal Team, at the California Public Utilities Commission. A. J. acknowledges support from an EPA-STAR Graduate Fellowship.

References

Castells, M., 1996. The Rise of the Network Society v1: The Information Age: Economy, Society and Culture, Blackwell Publishers, pp. 155–168.

Gastwirth, J.L., Glauberman, M., 1976. Econometrica 44, 479.

Jacobson, 2004. Rural electrification with solar energy in Kenya, Tegemeo Project Working Paper Series, http://www.aec.msu.edu/agecon/fs2/kenya/

Lubchenko, J., 1998. Science 279, 491.

Saboohi, Y., 2001. Energy Policy 29, 245–252.